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Uncertainty and Financing Constraints

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Abstract. Using a panel of Dutch listed firms this paper provides empirical evidence for the hypothesis that more risky firms are confronted with more severe capital market constraints than relatively less risky firms. The paper also contributes to the discussion on the usefulness of cash flow as a measure of financial constraints. We present a stochastic version of the Kaplan-Zingales (1997) model. We show that cash flow sensitivity can be used as a meaningful indicator of financing constraints if firms are classified by the degree of uncertainty they face and if the uncertainty originates from cost uncertainty.

Key words: financing structure, investment, uncertainty

JEL classification codes: E22, G32.

1. Introduction

In the last decade new insights with respect to investment theory center around two themes: the role of capital market imperfections and the effect of uncertainty on irreversible investment. The capital market imperfections literature shows that corporate investment is sensitive to internal funds if financial constraints are effective. In a world with perfect capital markets, firms will be indifferent with respect to financing investment with internal or external funds (Modigliani and Miller 1958). However, it is well known that financial markets are normally characterized by imperfections related to asymmetric information problems, such as monitoring and screening issues (Jensen and Meckling 1976; Stiglitz and Weiss 1981; Myers and Majluf 1984). Under asymmetric information the Modigliani-Miller proposition no longer holds and investment depends on the financial structure.

The investment under uncertainty literature focuses on the importance of uncertainty with respect to selling price, sales, stock prices, etc. on investment. Orthodox studies on investment and uncertainty show that a competitive risk neutral firm is positively affected by uncertainty as long as the marginal productivity of capital

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is a convex function of prices, which will be the case for a constant returns to scale production function (Hartman 1972; Caballero 1991). The more recent real option approach to investment under uncertainty (see Dixit and Pindyck 1994) argues that it is more likely that uncertainty affects investment negatively. This literature emphasizes the importance of the irreversibility of investment and the option value of waiting to invest. The option value of waiting probably increases if uncertainty of the underlying investment project increases, leading to a negative effect of uncertainty on investment. However, the option approach to investment under uncertainty can also explain a nonlinear investment-uncertainty relationship (Sarkar 2000). Most empirical studies find a negative linear investment-uncertainty relationship though (see Lensink, Bo and Sterken 2001).

Both lines of research resulted in important new insights with respect to the modeling of investment. There are some theoretical attempts to integrate the two lines of theory, see e.g., Lensink and Sterken (2002). However, quite surprisingly, there is no empirical literature available that tries to combine them, although it is apparent that uncertainty and capital market imperfections are interlinked. This is obvious if debt holders are risk averse, since then higher uncertainty, leading to more risky projects, will result in an increase of the risk premium. However, this will also be the case with risk neutral debt holders due to limited liability. Equity holders of a firm have an incentive to select projects with higher risks if investments are partly financed by debt. Rational debt holders, however, will anticipate this behavior and charge an interest premium that reflects the expected costs they must bear in the event of default. Therefore, equity holders will ultimately bear the costs of more uncertainty in the form of an increase in the wedge between internal and external financing costs.

The purpose of this paper is to empirically explore the abovementioned relationship between uncertainty, capital market imperfections and investment using a panel of Dutch firms. Note that we do not aim to disentangle all possible relationships between capital market imperfections, uncertainty, and their effect on investment. Rather, we focus on one possible way in which uncertainty and capital market imperfections are interlinked. More specifically, we argue that a group of relatively risky firms, i.e., firms that are faced with higher degrees of uncertainty, will suffer more from financial constraints than a group of relatively safe firms. Consequently, an increase in uncertainty (risk) will have an indirect negative effect on investment via more severe capital market constraints.

Section 2 describes the general methodology of the empirical models of investment under capital market constraints. The approach basically compares the elasticity of investment with respect to a measure of internal funds, say cash flow, for different groups of firms. A higher elasticity suggests more severe capital market constraints. This approach is popularized by Fazzari, Hubbard, and Petersen (FHP) (1988), and now used by a long list of authors (for a survey, see Lensink, Bo and Sterken 2001). Although numerous researchers have followed the methodology of FHP, it is not undisputed. Some authors question the relevance of the use of investment-cash flow sensitivity as a measure of financial constraints. To assess our results carefully it is important to have a closer look at this critique. Kaplan and Zingales (1997) (KZ) criticize the FHP approach by pointing out that it is only meaningful to look at differences in the elasticity of investment with respect to cash flow if the investment-cash flow sensitivity is monotonically increasing with respect to the indicator used to classify firms. In Section 3 we present a stochastic version of the model proposed by KZ and examine to what extent the KZ-critique also holds for our model. Assuming that a manager behaves in line with a constant absolute risk aversion utility function we show that our approach does not suffer from the KZ-critique. Consequently, this paper also contributes to the discussion on the usefulness of using cash flow sensitivities as measures of financial constraints.

Section 4 describes our data set. It contains 96 Dutch listed firms covering the period 1985–1997. The section also presents a graphical description of the data, which shows that firms facing higher uncertainty (no matter what the source of the uncertainty might be) experience larger investment-cash flow sensitivities. This provides a first indication that firms faced with higher degrees of uncertainty are more capital market constrained. Sections 5 and 6 are the main parts of the paper, presenting two sets of estimation results with respect to the effect of uncertainty on investment are presented. In Section 5 we use an endogenous threshold approach. The argument to use this approach runs as follows. The FHP approach requires that firms can be divided into sub-samples based on criteria that identify ex ante the firms that face the most severe financial constraints. In our case, we classify firms on the basis of the degree of uncertainty. One of the main problems with this approach is that the threshold variable used to split the entire group of firms is exogenous. In Section 5 we try to circumvent this problem by estimating a threshold investment model as suggested by Hansen (1999). The main advantage of the Hansen approach is that the estimates of the thresholds are conditional on the model specification as a whole. We find that more uncertainty leads to larger investment-cash flow sensitivities, indicating more severe capital market constraints for the group of firms with risky projects. There is, however, a drawback to using the Hansen-procedure, as it is in fact a simple Least Squares strategy, not allowing for endogeneity of the regressors. Since the assumption of fully endogenous regressors seems too restrictive, Section 6 analyzes the results further using the Generalized Method of Moments (GMM) estimator. We base our classification of firms on the results obtained in Section 5. The GMM results also confirm our hypothesis that firms faced with higher degrees of uncertainty will suffer more from capital market imperfections. Finally, Section 7 summarizes and concludes the paper.

2. The FHP Methodology

The methodology we use follows the recent empirical literature that examines the effects of capital market imperfections on investment. This literature, based on the idea that investment is only sensitive to internal funds if there are capital market constraints, examines to what extent a proxy of internal funds (cash flow) affects investment. As Chirinko (1993) argues, one might use a reduced-form q-model of investment (see FHP 1988) or estimate Euler-conditions to analyze the impact of financial variables on investment decisions (see e.g., Whited 1992). In the reduced form investment model a measure for internal funds is directly included as one of the regressors. In the Euler approach, measures of internal funds indirectly affect investment via a Lagrange multiplier. The Euler approach has the advantage that future profitability, like marginal q, does not need to be specified. On the other hand the Euler model incorporates dynamics, which can complicate estimation (see Whited 1992, for a detailed discussion).

We base our empirical analysis on the reduced-form cash flow model and proceed with an exposition of this model. The major theoretical notion of the standard investment-cash flow model is the upward sloping supply curve of financial capital with internal resources as the cheapest funds (see Duesenberry 1958). The higher the cost difference between internal and external funds, the more a firm will have to rely on its own funds. Since investment-cash flow sensitivity is generally significant and positive for all firms, most of the literature takes the following approach. The sample is divided according to an a priori measure of financing constraints (such as firm size, age, dividend-payout ratio, business group affiliation etc.), whereafter the investment-cash flow sensitivities of the different sub-samples are compared (see, e.g., FHP, Hoshi et al. 1991, and Hu and Schiantarelli 1998). Higher cash flow sensitivity is seen as evidence of tighter capital market constraints.

The primary innovation of our paper is the classification of firms. We argue that firms that are faced with more uncertainty (the risky firms) will suffer more form financing constraints. Therefore, we classify firms into a group facing high and low uncertainty (measured via different indicators). Subsequently, we compare cash flow sensitivities of both groups in order to test whether firms with high uncertainty suffer more from capital market constraints.

Although numerous researchers have followed the above-mentioned methodology, it is not undisputed. The main critique focuses on three issues; the (time independent) a priori classification of firms in different groups, the problem that internal funds may also proxy for the profitability of investment and the use of investment-cash flow sensitivity as a measure of financial constraints. To judge our results it is important to have a closer look at these points of critique, and to explain how we deal with them in the empirical analyses. We deal with the first two items in this section and leave the last point to the discussion of our theoretical innovation in Section 3.

An *a priori* classification of firms is problematic since the threshold used to classify firms in different groups is set arbitrarily. Moreover, although it might be possible to identify constrained firms, it is quite often impossible to identify the years during which a firm is constrained. This makes it impossible to differentiate between firm-specific effects on investment and the effects of financing constraints (see KZ 1997). To account for this point of critique, we use an endogenous splitting method, the so-called threshold estimation technique developed by Hansen (1999), in Section 5.

Some authors argue that the relationship between investment and measures of the availability of internal funds may suffer from the fact that internal funds may proxy for the profitability of investment. In that case, a positive relationship between internal funds and investment may be expected since firms with more liquidity are doing well and have better investment possibilities (Hoshi, et al. 1991). This may imply that the cash flow coefficient cannot be interpreted in terms of capital market imperfections. The usual way to get around this problem is to add Tobin's q or the market-to-book ratio as an independent variable in the model, and that is exactly what we will do in the empirical analyses in Sections 5 and 6.

3. Are Investment-Cash Flow Sensitivities Useful Measures of Financing Constraints?[1]

In the literature there is an ongoing discussion of the usefulness of investment-cash flow sensitivities as measures of financing constraints. Some authors (including ourselves) follow FHP and argue that a comparison of investment-cash flow sensitivities for different groups of firms provides a good indication of the (difference in) severity of financial constraints which these firms are faced with. This literature is closely related to the broader "imperfections" literature, which studies adjustment costs and (ir)reversibilities, monopolistic competition on product markets, and lack of information on financial markets. Such imperfections might result in an increase in the sensitivity of investment to changes in internal wealth e.g., via cash flow (see Stein 2001).

Others oppose the use of cash flow as a measure of financing constraints. Cleary (1999), for instance, argues that a large cash-flow sensitivity of investment may also signal financial soundness of the firm. Knowing its financial strength and ability to attract external funds, the firm first uses cash flow to finance investment. The most prominent critics are Kaplan and Zingales (1997). They argue that it is only meaningful to look at differences in the elasticity of investment with respect to cash flow if the investment-cash flow sensitivity is monotonically increasing with respect to the indicator used to classify firms. They provide a theoretical example that shows that for several classification schemes strong investment-cash flow sensitivity signals financial constraints in only very specific cases (with particular specifications of production and cost functions). FHP (2000) react to the KZ critique by disputing their operational definition of financing constraints as well as by pointing out some problems related to the way KZ classify firms into financially constrained and unconstrained firms.

There is still no consensus on the issue of investment-cash flow sensitivities today and we certainly do not try to provide a definite answer in this paper. However, we do provide a contribution to the discussion by analyzing an adjusted

[1] The model presented in this section draws on the Kaplan-Zingales (1997) model.

version of the model originally developed by KZ. There are various arguments to support starting from the KZ-model. First, the model is simple and can be easily explained. Secondly, KZ illustrate that their **deterministic** model shows that strong investment-cash flow sensitivity is not necessarily a signal of financial imperfections. We will therefore examine for our classification of firms under which conditions differences in cash flows are meaningful measures for financial constraints. In order to be able to do this we need to develop a stochastic version of the KZ model.

3.1. THE MANAGER'S UTILITY FUNCTION

Although a manager's attitude towards risk is one of the salient characteristics that show up in many analyses, there are only a few attempts to empirically measure the risk attitude of managers. The most relevant general empirical literature on risk attitudes is the experimental literature (see, for example, Kahneman and Tverski 1979). However, this literature is still in its infancy and often does not apply to firm managers. Nevertheless, it is commonly assumed that managers are risk averse. This insight comes from the recent literature on ownership and control (for an overview, see Grinblatt and Titman 2002). This literature emphasizes that investment policies may differ if self-interested managers or outside shareholders control investment choices. An important insight from this literature is that managers are assumed to be risk averse. The main reason why self-interested managers are assumed to be risk-averse is the fear of bankruptcy. It is even argued that managers have a tendency to be more risk averse than shareholders. The reason is that outside shareholders can avoid unsystematic risk by means of diversification. However, the probability of a firm getting into financial trouble is affected by systematic and unsystematic risk. Therefore, for managers systematic and unsystematic risk is of importance because both affect the probability of the manager retaining his or her job. For this reason, we assume that the manager acts according to a risk-averse utility function.

If a manager demonstrates risk aversion she will act according to optimizing the expected value of a concave utility function E[$U(x)$], where x denotes wealth, and $U'(.) > 0$ and $U"(.) < 0$. A certainty equivalent CE of the expected value of x, which we denote by x^e, is defined by $CE = x^e + p$, where p is the risk premium. For all $z = x - x^e$, the following condition needs to hold: $U(x^e - p) =$E[$(U(x^e + z)$]. Using a second-order Taylor expansion and assuming small risks (see e.g., Gollier 2001), it is easy to see that $p = -R_a(x)/2$ E[x^2], where p is sometimes called risk compensation and $R_a(x)$ is the Arrow-Pratt measure of absolute risk aversion. If absolute risk aversion $R_a(x)$ of an agent is decreasing in x, then he or she has *decreasing absolute risk aversion*. If $R_a(x)$ is constant (increasing) in x, the agent has *constant* (*increasing*) absolute risk aversion.

As argued above, the literature is quite clear about the assumption that managers are risk averse. However, the literature does not give much guidance as to whether a manager's absolute risk aversion is constant, increasing or decreasing. The reason for this is clearly stated by Laffont (1993) in his chapter on "Measuring risk aversion and risk". He concludes that it is very difficult to obtain sufficient information about an agent's preferences, to know whether his or her absolute risk aversion increases or decreases. The main argument is that this requires information about the third derivative of the manager's utility function. There are only a few empirical studies available that have tried to measure whether absolute risk aversion increases or decreases in wealth (see, for instance, Binswanger 1980 and Hartog et. al. 2000). This literature seems to conclude that decreasing absolute risk aversion gives the best representation of agent's behavior However, it should be noticed that the few exceptions available do not deal with firm managers. For management decisions it may be argued that the size of personal wealth is not so relevant to the attitude towards risk.

Because of the lack of empirical evidence on the exact type of risk aversion, in theoretical papers all types of utility functions are found. Therefore, the choice for a particular utility function is primarily driven by its ability to derive analytical results, and not so much because of its success in correctly representing the attitude towards risk of agents in the real world. The most frequently used utility functions in economic models form part of the so-called set of harmonic absolute risk aversion (HARA) utility functions (see Gollier 2001). The HARA class includes the constant relative risk aversion (CRRA), the constant absolute risk aversion (CARA) and quadratic utility functions.

We use a CARA utility function. Although the choice of this utility function is arbitrary and other specifications exist (see Saha 1997), the CARA-class is widely used (see Blanchard and Fischer 1989). For a positive risk premium the assumption of constant absolute risk aversion implies utility functions of the exponential class (see Pratt 1964). This class of utility functions has often been used to model portfolio decisions (see Hendershott 1971, and Courakis 1988). In addition, some papers have used a CARA utility function to estimate the risk attitude of producers, see for instance Antle (1987). Although constant absolute risk aversion may be a less plausible description of risk aversion than constant relative risk aversion (or decreasing absolute risk aversion) the CARA specification is analytically more convenient in our case. For this type of utility function the expression for the risk premium is simple and only depends on the variance of the key 0wealth variable. It should be noted, however, that the assumption of constant absolute risk aversion is a very simplified approximation. The exponential utility function class has the main advantage of simple derivations, but it has also a main disadvantage of leading to specific results, which do not hold in general cases. This also holds for our analysis hereafter.

3.2. THE MODEL

Our manager derives utility from real profits (π) according to the exponential utility function $U(\pi) = a - ce^{-\alpha\pi}$, where U is utility and a, α and c are parameters. Profits are stochastic: $\pi \sim \mathrm{N}(\mu_\pi, \sigma_\pi^2)$, where μ_π is the mean and σ_π^2 is the variance. The manager is assumed to maximize the expected value of utility which, given the normality assumption, can be shown to be equal to:

$$E[U(\pi)] = a - c\left[\exp\left(\frac{-\alpha}{2}\mu_\pi + \left(\frac{\alpha}{2}\right)^2 \sigma_\pi^2\right)\right] \tag{1}$$

where $E[.]$ is the expectation operator. For the CARA-class of utility functions this is equivalent to maximizing the certainty equivalent $\mu_\pi - \frac{\alpha}{2}\sigma_\pi^2$, because the coefficient of absolute risk aversion is $R_A = -\alpha$ (and $\alpha > 0$). This is one reason for our choice for the CARA-utility function. One can model risk neutrality by setting $\alpha = 0$. We model profits by:

$$\Pi = \lambda F(I) - vC(I - W, k) - I \tag{2}$$

Investment can be financed with internal funds W or external funds $E : I \equiv W + E$. The opportunity cost of internal funds is the cost of capital R, which is assumed to be equal to 1. The additional costs of external funds are given by a function $vC(E, k)$, where k is a measure of a firm's wedge between the internal and external cost of funds. The profit function (2) is similar to the one used by Kaplan and Zingales (1997). The difference is that we add a stochastic term λ for revenue F and a stochastic term v for costs C. λ represents uncertainty with regards to real returns on investment; v represents the stochastic nature of the cost of attracting external funds. We assume that:

A.1 :$E[\lambda] = E[v] = 1$ and $\sigma = E[\lambda^2]$ and $\rho = E[v^2]$

Note that we use the property that the variance of λ is equal to the variance of the simple deterministic transformation $\lambda + 1$. **A. 1** implies:

$$\mu_\pi = F(I) - C(I - W, k) - I \tag{3}$$

In line with the original Kaplan-Zingales model, we assume that the production function is concave:

A.2 :$F_1 > 0$, $F_{11} < 0$

Because of information or agency problems the use of external funds generates a deadweight cost for the issuing firm. The total cost of raising external funds increases with the amount of funds raised and the severity of the agency or information problems. We assume that:

A.3 :$C_1 > 0$; $C_2 > 0$; $C_{11} > 0$ and $C_{22} > 0$.

If both uncertainty terms are not correlated ($E[\lambda\mu] = 0$) we can derive the variance of profits:

$$\sigma_\Pi^2 = E[\lambda^2]f(I)^2 + E[v^2]C(I - W, k)^2 = \sigma F(I)^2 + \rho C(I - W, k)^2 \quad (4)$$

The first-order condition for optimal investment is:

$$[(1 - \alpha\sigma F(I))F_1(I)] = 1 + (1 + \alpha\rho C(I - W, k))[C_1(I - W, k)] \quad (5)$$

Total differentiation of this condition, ignoring dk, gives:

$$[(1 - \alpha\sigma F)_{11} - (1 + \alpha\rho C)C_{11} - \alpha(\sigma F_1^2 + \rho C_1^2)]dI$$
$$= -[(1 + \alpha\rho C)C_{11} + \alpha\rho C_1^2]dW \quad (6)$$

In the remainder of this section, we analyze the cost and return of uncertainty separately, by setting ρ or σ, respectively, equal to zero. Specifically, we examine whether the investment-cash flow sensitivity is monotonically increasing with respect to uncertainty, our indicator for classifying firms. Only if this is the case, will the difference in cash-flow sensitivity be a meaningful measure for financial constraints.

PROPOSITION: Under A. 1–A. 3 an increase in cost uncertainty leads to a higher investment-cash flow sensitivity for a risk-averse manager. The effect of an increase in return to investment uncertainty is ambiguous. For a risk-neutral manager, an increase in uncertainty does not affect the investment-cash flow sensitivity.

Proof. For cost uncertainty, the effect of an increase in uncertainty is given by:

$$\frac{d^2I}{dWd\rho} = \frac{-(CC_{11} + C_1^2)\alpha F_{11}}{(C_{11} + \alpha\rho CC_{11} - F_{11} + \alpha\rho C_1^2)^2} > 0 \quad (7)$$

For return uncertainty, the effect of an increase in uncertainty is ambiguous and given by:

$$\frac{d^2I}{dWd\rho} = \frac{-\alpha(F_1^2 + FF_{11})C_{11}}{(\alpha\sigma(F_1^2 + FF_{11}) + C_{11} - F_{11})^2} \quad (8)$$

It is immediately clear that for the risk-neutral manager ($\alpha = 0$) both derivatives are equal to zero.

QED

Equation (7) shows that the sensitivity of the internal wealth dependence of investment *dI/dW* increases if cost uncertainty ρ increases. So risk-averse managers offset a higher cost uncertainty by increasing the fraction of internally financed investment (external finance being costly). For revenue uncertainty there is no clear interpretation. The concave revenue function allows managers to benefit from more revenue uncertainty on the one hand, but on the other it might again be more attractive to offset the increase of risk and rely more on internal finance.

To conclude, our model shows that for reasonable assumptions investment-cash flow sensitivities provide a useful measure of financing constraints if it is assumed that the manager is risk averse, and if uncertainty mainly originates from uncertainty in costs. So, in a stochastic world, and assuming that firms are classified on the basis of different degrees of uncertainty, the cash flow measure seems to perform better as a measure for financial constraints than argued by KZ. This provides support for the FHP methodology. However, it should also be noted that if the uncertainty originates from uncertainty in revenues, our analyses suggests that cash flows are only useful measures for financing constraints if additional assumptions with respect to the production function and the cost function are made. This does not contradict our main hypothesis, since in reality these conditions may be fulfilled. However, it does imply that we should be careful in our interpretation of the results.

4. Data

We use a panel of Dutch listed firms to empirically test our hypothesis. During the period 1985–1997 about 150 firms were listed on the Amsterdam Stock Exchange. From these firms we use the non-financial firms and remove some firms that have exceptional accounting systems (like Royal Dutch Shell, which publishes its accounts both in the United Kingdom and the Netherlands). This sampling yields a set of 112 firms. The coverage of the data for the starting years of the sample and the most recent years is not complete though. Moreover, we use moving averages for some variables in the specification of our model. Finally we need a balanced set of data in one of our regression models, namely the threshold model presented in Section 4. This restricts the final data set to 96 firms over 1990–1997. This set is considered to be representative for the Dutch non-financial manufacturing sector.

The data are taken from the source REACH, which is maintained by the Belgian company Bureau Van Dijk. Bureau van Dijk publishes a European equivalent AMADEUS, which contains information on both listed and non-listed firms. REACH is the Dutch subset of AMADEUS and includes more than ten thousand Dutch firms. Our main rationale for considering listed firms is twofold. Firstly, the way of presenting financial results is comparable among listed firms. Secondly, we are interested in the impact of stock price volatility on firm investment and so need stock market prices.

From the balance sheet and profit and loss account we construct the variables listed in Table I. Sales (SALVOL) and employee volatility (EMPVOL) are based on the observations from $t-6$ up to and including t (7 years in total). We calculated a rolling coefficient of variation (mean over the standard deviation) using these 7 observations.

Table I. Definitions of variables.

CF	cash flow (equals net profits plus depreciation);
EMP	number of people employed;
EMPVOL	volatility of employees (see measurement *SALVOL*)
EQ	equity;
EQVOL= 100*(*HIGH/LOW*−1)	stock price volatility;
HIGH	highest stock price during the year;
I	capital expenditure in material fixed assets;
K	material fixed assets;
LIQ	liquid assets;
LOW	lowest stock price during the year;
MB = *MV/EQ*	market-to-book ratio;
MV	market value of equity at the end of the year (= stock price * number of shares outstanding);
SAL	sales;
SALVOL	volatility of sales, measured by a 7-year window coefficient of variation of sales;
TA	total assets;
WC	working capital: short-term assets minus short-term liabilities.

Table II. Descriptive statistics.

	Mean	St.dev.	Median
$I/K(-1)$	24.40	16.97	19.10
CF/K(−1)	42.18	16.38	33.55
EQ/K(−1)	138.44	34.91	110.75
WC/K(−1)	75.21	30.54	45.06
d(*WC*)/*K*(−1)	3.51	27.29	2.04
LIQ/K(−1)	42.39	19.72	12.13
$SAL(-1)/K(-1)$	665.98	148.85	427.61
MB	2.45	1.46	1.53
EQVOL	60.20	33.85	43.92
SALVOL	21.56	8.09	19.21
EMPVOL	18.80	8.33	15.60

See Table I for an explanation of the symbols used.
Source: REACH (Bureau van Dijk 2001).

Table III. Correlation matrix of the volatility variables.

	EQVOL	*SALVOL*	*EMPVOL*
EQVOL	1	0.164	0.111
SALVOL	0.164	1	0.639
EMPVOL	0.111	0.639	1

Note that these figures present stacked correlation coefficients (96 firms times 8 years = 768 observations). All correlation coefficients are significant at the 99 percent confidence level (so p-values of the hypothesis of a zero correlation are almost equal to zero).

Table II presents descriptive statistics of the variables used in the models to be discussed below. The figures represent averages (medians) of firm' averages (medians) over the years. We first average over the years per firm and again take averages of the average firm observations (and medians of medians). Table II shows that the data are not seriously skewed, since the mean and median values coincide. The first panel presents the major investment data. The average ratio of capital expenditure to the stock of material fixed assets is a little over 20 per cent. Cash flow as a percentage of material fixed assets is around 40 per cent. On average the amount of working capital is relatively large. During the 1990–1997 period most firms had a high market-to-book ratio. Most listed firms tried to restore their solvency during the period 1985–1997 and succeeded in doing so. Stock price volatility is rather large. Here we emphasize that our measure of volatility (high minus low) can be rather sensitive to shocks in equity prices. Inspection of our data however reveals that the high-low volatility is supported by observations in our whole sample period. For the other measures of volatility the coefficients of variation have rather modest means (median values) of about 20 per cent.

For our purpose we need to describe the uncertainty measures more precisely. Table III gives the correlation matrix, which shows that the stock price volatility is less (but still significantly) correlated with the other measures. The correlation between sales and employee volatility is higher. So we expect the differences in results for stock price volatility on the one hand and sales and employee uncertainty on the other.

A natural and convenient way to describe the data is through the use of scatterplots of investment, cash flow and uncertainty, which may reveal non-linearity. A simple correlation plot of the investment and cash flow ratios does not reveal the information we want to illustrate, since investment depends on other firm specific variables. We need to control for these firm specific effects, so we proceed as follows. First we estimate our base reference model (see also Section 4). We regress I/K on Market-to-Book (MB), the change in working capital ($d(WC)/K(-1)$),

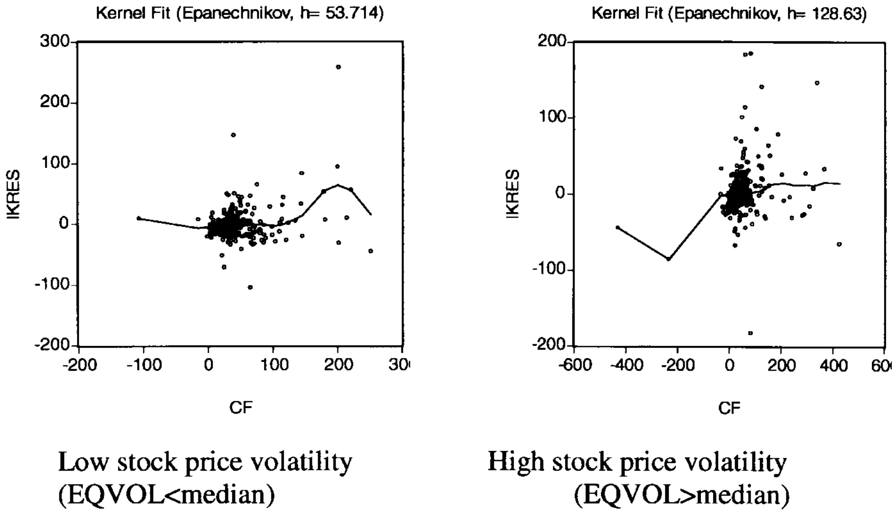


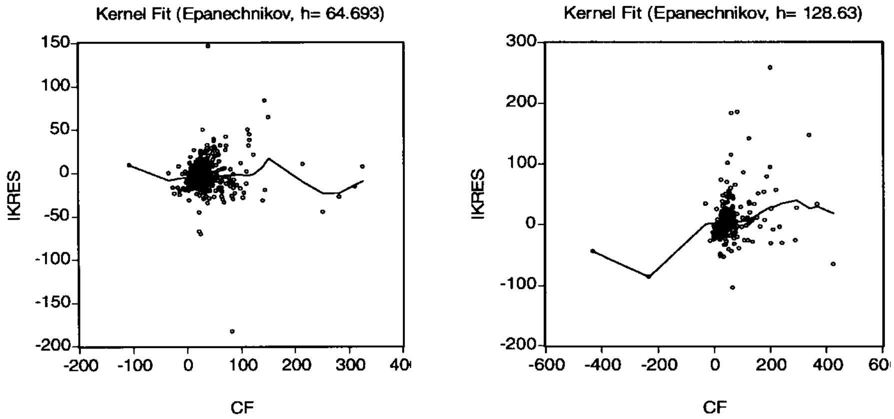
Figure 1. Investment-cash flow plots for low and high stock price volatility.

lagged sales $(SAL(-1)/K(-1))$, the lagged investment ratio $(I(-1)/K(-2))$ and an intercept. We use the residuals from this estimated equation as the "conditioned" investment data. Next we scatter these residuals with cash flow $(CF/K(-1))$ for low and high volatility separately. This gives us an impression of the properties of the data.

Figure 1 shows the results for stock price volatility. The left panel shows the observations with stock price volatility below the median value and the right-hand panel plots the observations with stock price volatility above the median value. On the vertical axis we plot the residuals of the simple OLS equation and on the horizontal axis the variable $CF/K(-1)$. We expect the slope of the high uncertainty plot to be steeper. The line in the Figures represents a local linear Kernel fit.[2] We did not trim the observations for outliers and the scale is different on both axes. Figures 2 and 3 provide similar plots for low and high sales and employment volatility. All the plots give a similar impression: the investment-cash flow sensitivity is higher for higher volatilities: the slopes of the right-hand side curves are steeper on average. Stock price volatility plots are the least convincing in this respect due to the peculiar shape of the low-volatility line.

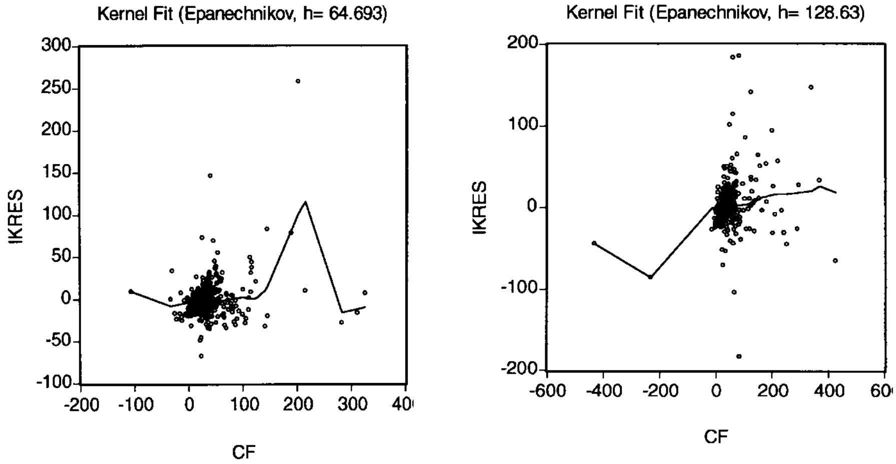
The descriptive statistics point at differences with respect to the investment-cash-flow sensitivities between regimes of low and high volatility. This provides a first indication of the relevance of our claim that firms faced with high uncertainty are more troubled by capital market constraints. In the remaining sections we examine this observation in more detail.

[2] This view displays fits of local polynomial kernel regressions of the first series Y on the second series X in the group. The kernel fits are nonparametric regressions that fit local polynomials. The kernel is the function used to weight the observations in each local regression. We use the Epanechnikov kernel.



Low sales volatility (SALVOL<median) High sales volatility (SALVOL>median)

Figure 2. Investment-cash flow plots for low and high sales volatility.



Low employment volatility (EMPVOL<median) High employment volatility (EMPVOL>median)

Figure 3. Investment-cash flow plots for low and high employment volatility.

5. Threshold Estimation

We argue that investment, cash flow and uncertainty are interrelated. Our hypothesis is that uncertainty affects investment by means of capital market imperfections. Firms that are faced with more uncertainty, say the more risky firms, will have greater difficulties in communicating their information to their lenders, so that fluctuations in investment spending of these risky firms, in comparison to relatively less risky firms, will be more closely linked to changes in the availability of internal funds (cash flow).

In this section we explore this relation empirically by considering the investment-cash flow sensitivity for two groups of firms, classified by means of a threshold level for uncertainty. The main argument put forward in this section relates to the endogeneity of the cut-off level of uncertainty. In the previous section we took the median values of the volatility variables to be the "exogenous" cut-off levels. Here we integrate the cut-off level into the model and determine the cut-off level of uncertainty simultaneously with the parameters of the model. We do so using an estimation method proposed by Hansen (1999). Hansen provides an estimation method to allow for different regression functions across subclasses of observations. Hansen applies his estimation technique to the FHP investment-cash flow model. He finds that low-debt firms have lower investment-cash flow sensitivity than highly indebted firms. We want to model similar investment-cash flow sensitivities for different levels of uncertainty measures. We propose to estimate such a threshold regression model for $i = 1, \ldots, n$ firms and $t = 1, \ldots, T$ observations of the following form:

$$\left(\frac{I}{K}\right)_{it} = \alpha' z_{i,t-j} + \beta_1' CF_{it} I(V_{it} \leq \theta) + \beta_2' CF_{it} I(V_{it} > \theta) + \epsilon_{it} \qquad j = 0, 1 \tag{9}$$

where I represents net capital expenditure, K the beginning-of-period capital stock, z is the vector of so-called regime-independent (or control) variables (which might include fixed effects); CF is the so-called regime dependent variable (cash flow as a percentage of the beginning-of-period capital stock); α, β_1, and β_2 are (vectors of) parameters; and the error term ϵ_{it} is i.i.d. with mean zero and finite variance.[3] The threshold variable V is the uncertainty measure, and θ is the threshold value of the uncertainty measure to be estimated, which does not depend on the firm or year. $I(.)$ represents the indicator function, which has the value one if the argument is true and zero otherwise. So the threshold variable defines two regimes: a low uncertainty regime with $V_{it} \leq \theta$ and a high uncertainty regime with $V_{it} > \theta$. The importance of the Hansen estimator is that all parameters are determined simultaneously with the determination of the threshold value of the uncertainty measure. Hansen proposes a panel estimation method using a fixed-effects transformation. Crucial in this method are the asymptotics of the confidence levels of the thresholds. Hansen proposes procedures to determine the confidence levels based on inverting the loglikelihood-ratio statistic (see for further details Hansen 1999). Based on the predictions of the standard cash flow model, we expect that if uncertainty is below the threshold, the investment-cash flow sensitivity is low and hence the firm is probably investing less than proportionally. But if uncertainty exceeds the threshold level, the investment-cash flow sensitivity increases. This suggests that the estimated coefficients for β_1 and β_2 are expected to differ. In

[3] As noted by Hansen (1999) this assumption excludes lagged dependent variables from the model.

other words, cash flow may have different effects on firm investment depending on the magnitude of the volatility effect.

The empirical model is estimated using conditional least squares. To that end the observations are sorted on the threshold variable and the sums of squared residuals are computed for all values of the threshold variable. The optimal value of the threshold variable is the one that minimizes the sum of squared residuals. The optimal parameter estimates are the estimated α's and β's that belong to this optimal threshold value. An important question is whether the threshold regression model is statistically significant to its linear counterpart, which has the null hypothesis H_0: $\beta_1 = \beta_2$. In this case the threshold parameter is not defined under the null hypothesis, which makes the testing problem complex. However, Hansen (1996) shows that asymptotically valid p-values can be constructed by bootstrapping.[4] Hansen also suggests that one should test for the number of thresholds. This implies that the model with one and with no threshold should be compared, as well as the specification with two and with a single threshold.

To apply the Hansen estimator a few empirical choices have to be made. First, we need to decide on the choice of the control variables z. Here we closely follow Houston and James (2001) in specifying an investment model by taking:

1. MB: the market-to-book value of equity. This variable is a proxy for Tobin's q. This variable is included to control for the fact that internal funds may proxy for the profitability of investment, a major critique of the standard cash flow model. Note that the variable we use to proxy for Tobin's q is theoretically less appealing than Tobin's q itself, but it has the advantage that it can be measured quite precisely. There is no information on the market value of debt whatsoever, which complicates any specification of q;
2. $SAL(-1)/K(-1)$: lagged sales over capital. This variable is included to pick up the impact of past demand for final output on the investment decision. It also proxies for future profitability;
3. $\Delta(WC)/K(-1)$: cash flow might have another simple destination: the change of working capital. This variable competes with capital expenditure;
4. $LIQ/K(-1)$: the stock of liquid assets gives an indication of the availability of short-term funds.

[4] Valid confidence intervals for the threshold parameter can be based on the likelihood ratio (or F) statistic $LR(\theta) = (S(\theta) - S(\hat{\theta}))/\hat{\sigma}^2$, which tests the null hypothesis H_0: $\theta = \hat{\theta}$. Here $S(\theta)$ is the sum of squared errors of the estimated threshold regression when the threshold parameter equals θ, $S(\hat{\theta})$ is the sum of squared residuals belonging to the optimal threshold parameter $\hat{\theta}$, and $\hat{\sigma}^2$ is the residual variance belonging to the optimal threshold parameter $\hat{\theta}$. The likelihood ratio statistic is equal to zero at $\theta = \hat{\theta}$. Confidence intervals for the threshold parameter can be constructed by inverting the distribution function of the likelihood ratio statistic. A graphical method to find the confidence interval of the threshold parameter is to plot the likelihood ratio statistic $LR(\theta)$ against all values of θ and to check for which values of θ crosses the horizontal line that shows the confidence level of the test. Confidence intervals of the other parameters in the threshold regression, the α's and β's, can be approximated by the conventional normal approximation as if the threshold estimate $\hat{\theta}$ were the true value.

The second empirical choice relates to the choice of the uncertainty measures as regime variable. We use three: stock price volatility (*EQVOL*), sales volatility (*SALVOL*) and employment volatility (*EMPVOL*). The first two measures are widely used in empirical studies on the investment-uncertainty relation. Employment volatility represents the uncertainty the firm faces with respect to attracting or firing of workers.

We are not interested in the fit of the linear model (the model that assumes equal parameter estimates across the two classes), so we don't report the results of the linear model in detail. It is important to note that the Hansen estimation method is a fixed effects method. We include time dummies (but don't report the estimation results). Table IV presents the results. The table shows that the Market-to-Book variable is a poor determinant of investment. This fact is widely described in the literature on investment (see e.g., Chirinko 1993). Lagged sales as a fraction of material fixed assets seems to provide a better proxy of future profitability. Liquid assets don't provide a clear contribution, but changes in working capital are a clear substitute for investment. The estimated values of the thresholds of all uncertainty measures are above the mean and median values (see Table II). This implies that the extreme sensitivity of investment to cash flow is found for the greater volatility firms. The table also gives an indication of the likelihood of a second threshold. For all models the improvement of the fit with a double threshold is not convincing, except for the stock price volatility model. Most importantly, the table shows that the cash-flow parameter for high volatility observations is about three times larger than the corresponding parameter for low volatility. This can be observed for all three models by looking at the lines labeled by CF(1) and CF(2). Table IV therefore illustrates that there is a differential impact of cash flow on investment depending on the degree of uncertainty that the firm is facing, suggesting that capital market constraints are more severe for the relatively risky firms.

6. GMM Estimation

The threshold estimation technique applied in the previous section is based on an OLS within-groups estimator. There is a serious drawback to this method since it assumes that the regressors are uncorrelated with the error term. When one of the regressors is correlated with the error term, the within-groups estimator provides biased and inconsistent estimates. That this will certainly be the case in a dynamic panel can be explained as follows. Assume a panel data investment model of the form $\left(\frac{I}{K}\right)_{it} = \alpha' z_{i,t} + \gamma \left(\frac{I}{K}\right)_{i,t-1} + n_i + e_{i,t}$, where n_i is an unobserved firm-specific effect. Since $\left(\frac{I}{K}\right)_{it}$ is a function of the permanent effect n_i, $\left(\frac{I}{K}\right)_{it-1}$, is also a function of n_i. Therefore $\left(\frac{I}{K}\right)_{it-1}$ is correlated with the error term, leading to a seriously biased OLS estimator if the model is estimated in levels. It is simple to show that the within transformation estimator, i.e., the fixed effects model, does not solve this problem. The within transformation of the investment model reads

Table IV. Threshold estimation results.

Dependent variable $I/K(-1)$	*EQVOL*	*SALVOL*	*EMPVOL*
MB	0.144 (0.148)	−0.066 (0.122)	−0.062 (0.118)
$d(WC)/K(-1)$	−0.238 (0.063)	−0.230 (0.063)	−0.225 (0.064)
$SAL(-1)/K(-1)$	0.008 (0.004)	0.009 (0.005)	0.009 (0.004)
$LIQ/K(-1)$	0.071 (0.044)	0.092 (0.051)	0.078 (0.050)
Threshold	114.29 (105.20;124.53)	39.16 (38.03,40.22)	51.82 (25.60;61.74)
CF(1)	0.108 (0.042)	0.106 (0.041)	0.102 (0.044)
CF(2)	0.308 (0.050)	0.313 (0.057)	0.344 (0.054)
LR(1)	38.95	24.92	20.71
SSR(0)	251700.23	251700.23	251700.23
SSR(1)	239551.24	240268.49	241091.65
SSR(2)	231873.29	240268.49	239961.37
Second threshold	34.78 (31.09;36.39)	21.58 (13.63;27.77)	12.34 (9.67;46.59)
LR(2)	25.43	11.25	12.74

Standard errors between parentheses. *CF*(1) gives the parameter estimate of the low-volatility regime, *CF*(2) gives the parameter estimate of the high-volatility regime, LR(1) denotes the likelihood-ratio test for the single threshold effect, LR(2) denotes the likelihood ratio of the double threshold effect, SSR(i) denotes the sum of squared residuals of the model with i thresholds. Time-dummies not reported. Confidence intervals based on 300 bootstrap-replications.

$$\left[\left(\frac{I}{K}\right)_{it} - \left(\frac{\bar{I}}{K}\right)_{it}\right] = \alpha'(z_{i,t} - \bar{z}_i) + \gamma\left[\left(\frac{I}{K}\right)_{it-1} - \left(\frac{\bar{I}}{K}\right)_{it-1}\right] + (e_{it} - \bar{e}_{it}) \tag{10}$$

in which a bar above a variable x denotes the average of the variable. Since $\bar{e}_{it}$ is an average containing e_{it-1}, which is correlated with $\left(\frac{I}{K}\right)_{it-1}$, $\left(\frac{I}{K}\right)_{it-1}$ is by construction correlated with $\bar{e}_{it}$. Therefore $\left[\left(\frac{I}{K}\right)_{it-1} - \left(\frac{\bar{I}}{K}\right)_{it-1}\right]$ will be correlated with $(e_{it} - \bar{e}_{it})$.

For this reason, we have not included a lagged dependent variable in the estimation of the threshold model. Since the investment decision is basically a dynamic problem, the I/K-ratio might be autocorrelated, which explains why so many empirical investment studies do account for a lagged dependent variable. However, this would need another estimation technique. Also in an investment model without a lagged dependent variable the regressors may be correlated with the error term. This will be the case if a subset of the regressors is endogenous, which is not unlikely. For instance, working capital (*WC*) is probably determined simultaneously with the investment rate (I/K). Then, the variable WC would be correlated with the error term, leading to a biased OLS estimator.

A standard method to deal with estimation problems with variables that are correlated with the error term is to use instrumental variables. Before we explain the method, it should be noted that in estimating the models we use information about the threshold values for the uncertainty measures as determined in the previous section. Ideally, the threshold should also be determined using the GMM routine. However, as yet there is no estimator available.

The instrumental estimation technique we use is the system-generalized methods of moments (GMM) estimator devised by Arellano and Bond (1998). In fact, we use a new version of DPD98. A method of moments estimator derives the coefficients from the so-called moment restrictions, i.e., restrictions on the covariances between regressors and the error term. The system GMM estimator of Arellano and Bond estimates a system combining two sets of equations. The system GMM estimator estimates a system combining two sets of equations consisting of a first differenced investment equation $\Delta\left(\frac{I}{K}\right)_{it} = \alpha'\Delta z_{it} + \gamma\Delta\left(\frac{I}{K}\right)_{it-1} + \Delta e_{it}$ and a levels equation

$$\left(\frac{I}{K}\right)_{it} = \alpha' z_{i,t} + \gamma\left(\frac{I}{K}\right)_{i,t-1} + n_i + e_{i,t}.^{5} \tag{11}$$

If it is assumed that the errors are independent across firms and serially uncorrelated, the following moment conditions can be used to obtain valid instruments for the lagged dependent variable in the first differenced equations:

$$E\left[\left(\frac{I}{K}\right)_{i,t-s}(e_{i,t} - e_{i,t-1})\right] = 0 \text{ for } s \geq 2;\, t = 3, \ldots T. \tag{12}$$

So, values of $\left(\frac{I}{K}\right)_{it}$ lagged two periods or more are valid instruments in the first differenced investment equation. The reason is that $\left(\frac{I}{K}\right)_{i,t-2}$ and earlier values are generally not correlated with $\Delta e_{i,t}$.

If the other regressor (z_{ijt}) is exogenous, then all the past, present and future values of z_{ij} are valid instruments. However, as argued above, there are several reasons to believe that the other regressors in the empirical investment model are endogenous, i.e., $E(z_{i,t}e_{i,s}) \neq 0$ for $s \leq t$. If this is the case, Arellano and Bond (1998) propose the following moment conditions for the differenced equations $E[z_{i,t-s}(e_{i,t} - e_{i,t-1})] = 0$ for $s \geq 2$; $t = 3, \ldots T$. This implies that values of $z_{i,t}$ lagged two periods or more are valid instruments if $z_{i,t}$ is endogenous. The whole history of the series in levels can be used as valid instruments for the first-differences. Note, however, that in models with endogenous regressors, using too many instruments in the later cross-sections could result in seriously biased estimates (Arellano and Bond 1998).

If the investment model contains a lagged dependent variable, and if the other regressor is endogenous, the following moment conditions are proposed by Arellano and Bond (1998) to be used for the levels equations:

$$E\left[\Delta\left(\frac{I}{K}\right)_{i,t-1}(\eta_i + e_{i,t})\right] = 0$$

and

$$E[\Delta z_{i,t-1}(\eta_i + e_{i,t})] = 0;$$

Valid instruments for the regressions in levels are the lagged differences of the corresponding variables. In this paper only the first-lag differences are used. Additional lagged differences would be redundant, because these are covered by the instruments of the first differences. Note that Δz_{it} could be used as an instrument in the levels equations if $z_{i,t}$ is strictly exogenous or predetermined.

The system GMM estimator is a two-step GMM estimator. In the first step, homoskedasticity and independent error terms are assumed. In the second step, these assumptions are relaxed by using a consistent variance-covariance matrix that is constructed from the first step residuals. A problem with the two-step estimator is that it has weak small sample properties, which would bias the standard errors downward. The estimator becomes inappropriate if a small number of cross-section units is combined with a large number of instruments, i.e., the number of time series units. In our case this could be problematic, since we only have 96 cross-section units (firms) and 8 observations per firm (1990–1997) in our data set, which might result in biased asymptotic inference. We address this problem in two ways. First, we present coefficients and t-values using the two-step GMM estimates, based on robust, finite sample corrected standard errors. Windmeijer (2000) shows how the two-step standard estimates can be corrected, and that is the approach we have followed.[6] Second, we do not use the whole history of lagged variables as instruments for the first differenced equations. After experimenting with different sets of instruments, we finally decided to only take the 2-period lagged levels of the variables as instruments for the first differenced equations. Note that in the estimates we also control for time effects by adding time dummies. These time dummies are used as additional instruments.

The reliability of the system GMM estimation procedure depends heavily on the validity of the instruments. We consider the validity of the instruments by presenting a Sargan test. The Sargan test is a test on overidentifying restrictions. It is asymptotically χ^2-distributed and tests the null hypothesis of the validity of the (overidentifying) instruments. p-values report the probability of incorrectly rejecting the null hypothesis: a p-value above 0.05 implies that the probability of

[6] We thank Windmeijer for providing us with the new version of DPD, including the two-step estimates with corrected standard errors.

incorrectly rejecting the null is greater than 0.05. In our case, a higher p-value makes it more likely that the instruments are valid. We also test the reliability of the instruments of the level equation by presenting the Difference Sargan test. The Difference Sargan test is calculated by subtracting the value of the Sargan test of a first differenced GMM estimate form the value of the Sargan test of the system GMM estimate. The degrees of freedom of the Differenced Sargan test equal the degrees of freedom of the system GMM Sargan test minus the first differenced Sargan test. The Differenced Sargan test is also asymptotically χ^2-distributed and tests the null hypothesis of validity of the (overidentifying) instruments in the level equation. The levels equations instruments are not rejected if the calculated value of the Differenced Sargan test is lower than the theoretical value of a χ^2 variable with n degrees of freedom. The consistency of the estimates also depends on the absence of serial correlation in the error terms. This will be the case if the differenced residuals display significant negative first order serial correlation and no second-order serial correlation. We present tests for first-order and second-order serial correlation related to the estimated residuals in first differences. The test statistics are asymptotically distributed as standard normal variables. The null hypothesis here relates to "insignificance" so that a low p-value for the test on first-order serial correlation and a high p-value for the test on second-order serial correlation suggests that the disturbances are not serially correlated. The serial correlation tests (M1 and M2 in the table) refer to the one-step GMM estimates.

The equations we estimate have the same structure as presented in the previous section. The lag structure is also the same as assumed in the previous section, as can be seen in Table V. The main difference is that here we do not endogenously determine the threshold, but instead use the threshold value to determine an indicator function with value 1 for the low volatility regime and 0 for the high volatility regime.[7] This indicator function is used to determine two cash flow variables, one for the high volatility regime and one for the low volatility regime. Another difference is that we now also add, in some of the regressions, the lagged dependent variable. The estimates are presented in Table V.

Although coefficient values differ for the threshold estimates and the GMM estimates, the main message remains: the cash flow coefficient is much higher for the high volatility regime than for the low volatility regime. This holds for all volatility measures used in the estimates. Note that the estimates without a lagged independent variable suffer from second-order serial correlation in the differenced residuals. Therefore, we have also presented estimates in which the lagged dependent variable is added as an additional regressor. For these estimates, there is no evidence for serial correlation. Moreover, the Sargan and the Difference Sargan test suggest that the instruments are valid. Most importantly, also the cash flow

[7] With respect to *EMPVOL*, we use the value of the lower confidence interval, instead of the average value of the threshold, to compute the indicator function. When the average value was used, the GMM estimates did not give any results due to problems with inverting the matrix, which is required for the two-step estimates.

Table V. System GMM estimates.

Dependent variable $I/K(-1)$	*EQVOL*	*EQVOL*	*SALVOL*	*SALVOL*	*EMPVOL*	*EMPVOL*
MB	0.203	0.198	0.011	0.018	−0.147	−0.175
	(0.169)	(0.179)	(0.108)	(0.123)	(0.188)	(0.179)
	[0.229]	[0.269]	[0.914]	[0.885]	[0.435]	[0.327]
$d(WC)/K(-1)$	−0.132	−0.140	−0.141	−0.127	−0.208	−0.185
	(0.065)	(0.059)	(0.046)	(0.042)	(0.087)	(0.075)
	[0.043]	[0.018]	[0.002]	[0.002]	[0.017]	[0.013]
$SAL(-1)/K(-1)$	−0.0001	−0.0001	−0.0004	−0.0006	0.0005	0.0007
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.956]	[0.961]	[0.874]	[0.782]	[0.848	[0.789]
$LIQ/K(-1)$	−0.019	−0.016	0.007	0.007	0.001	0.006
	(0.030)	(0.031)	(0.027)	(0.025)	(0.044)	(0.039)
	[0.521]	[0.594]	[0.791]	[0.780]	[0.974]	[0.876]
CF(1)	0.208	0.199	0.163	0.167	0.120	0.115
	(0.074)	(0.071)	(0.053)	(0.052)	(0.106)	(0.096)
	[0.005]	[0.005]	[0.002]	[0.001]	[0.260]	[0.230]
CF(2)	0.327	0.327	0.443	0.434	0.341	0.315
	(0.078)	(0.082)	(0.054)	(0.049)	(0.049)	(0.096)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$I(-1)/K(-2)$		0.082		0.059		0.120
		(0.066)		(0.061)		(0.071)
		[0.211]		[0.328]		[0.093]
Sargan	72.006	86.682	70.789	83.214	76.734	85.204
	[0.286]	[0.211]	[0.321]	[0.294]	[0.172]	[0.244]
Difference Sargan	28.93	34.47	29.98	36.19	34.51	53.45
	df = 36	df = 42	df = 36	df = 42	df = 36	df = 42
CV DS	50.71	57.84	50.71	57.84	50.71	57.84
M_1	−2.380	−2.864	−2.620	−2.964	−2.612	−3.101
	[0.017]	[0.004]	[0.009]	[0.003]	[0.009]	[0.002]
M_2	−2.583	−0.750	−2.043	−0.647	−2.504	−0.738
	[0.010]	[0.453]	[0.041]	[0.518]	[0.012]	[0.460]

Standard errors between parentheses; p-values between brackets. Sargan tests for the validity of the instruments in the differenced and levels equations; Difference Sargan tests for the validity of the instruments in the levels equation. df denotes degrees of freedom. CV DS denotes the critical value for the Difference Sargan (instruments are reliable if Difference Sargan is below CV DS). M_1 tests for the absence of first-order serial correlation in the first-differenced residuals; M_2 tests for the absence of second-order serial correlation in the first-differenced residuals. Time dummies are taken into account. They are not presented for reasons of space. *CF*(1) gives the parameter estimate of the low-volatility regime, *CF*(2) gives the parameter estimate of the high-volatility regime. In the first differenced equations, for all variables the lagged two period levels are used as instruments. For the levels equations, the one period lagged values of the first difference of all independent variables are used as instruments.

coefficient is also much higher for the estimates with the lagged dependent variable in the high volatility regimes.

7. Conclusions

This paper argues that firms that are confronted with a large degree of uncertainty will probably suffer from more severe capital market constraints. We test our hypothesis by following the methodology to estimate investment equations including a measure for internal funds (cash flows). In line with the literature we interpret a higher cash flow coefficient as an indication of more severe capital market constraints. We use two estimation procedures: a threshold panel least squares model estimates the threshold values for the uncertainty variables, and a Generalized Method of Moments estimator that allows for endogeneity of the regressors. The results of both estimation techniques provide support for our hypothesis for a panel of 96 Dutch listed firms.

This paper also contributes to the discussion on the usefulness of cash flow as a measure of financial constraints. We do this by analyzing a slightly adjusted version of the Kaplan-Zingales (1997) model. Following Fazzari, Hubbard, and Petersen (FHP) (1988) it is common to assume that a higher elasticity suggests more severe capital market constraints. However, several authors criticize this view by showing that it might be so that firms that do not face financial constraints will demonstrate higher investment-cash flow sensitivities. For example, Cleary (1999) argues that unconstrained firms might use their cash flow instantaneously for seemingly profitable investment projects knowing that they are able to attract external funds at any time. In addition, Almeida and Campello (2001) show that, as long as the firm is not fully unconstrained, investment-cash flow sensitivity will decrease if financial constraints become more severe. If current investment is seen as collateral for future borrowing and shocks to internal wealth affect current investment, firms that are less constrained will borrow more. So less constrained firms are more sensitive to cash flow through the amplification effect of collateral.

We do not attempt to fully solve this dispute. Nor do we try to come to a general conclusion as to whether the cash flow sensitivity is a useful measure for financial constraints. As such, our analysis does not shed a new light on the specific circumstances the above-mentioned authors are referring to. Our aim is much more limited. We examine whether an increase in the cash flow sensitivity can be associated with more capital constraints if firms are classified by means of the different degrees of uncertainty they face. We show that cash flow is a relevant measure if the uncertainty originates from cost uncertainty. Therefore, our contribution seems supportive of the main FHP conclusion that financial constraints are likely to imply large investment-cash flow sensitivities for firms. However, our analysis also provides some support for the critics of FHP by showing that additional assumptions with respect to the cost and production function are needed if the uncertainty originates from revenue uncertainty.

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